



Harnessing digital twin (DT) technology for food security and climate resilience in Sub-Saharan Africa (SSA)

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ABSTRACT

Sub-Saharan Africa (SSA) faces chronic food insecurity despite possessing approximately 60% of the world's uncultivated arable land. Field trials generate evidence but are costly and insufficiently scaled to address accelerating climate and demographic pressures. Digital twin (DT) technology, defined as the continuous, bidirectional virtual replication of physical systems using real-time data, supports monitoring, modelling, and optimisation of agrifood systems. To our knowledge, however, no published synthesis has examined DT agriculture research through the lens of SSA food systems or smallholder farming realities. A PRISMA-compliant systematic review was conducted across bibliographic databases using a pre-defined Boolean search and adapted PICOS eligibility criteria. Forty peer-reviewed studies published between 2019 and 2025 were included. Structured extraction captured bibliometric, geographic, methodological, technological, and technology readiness level (TRL) data, analysed using frequency tabulation and thematic clustering. DT agriculture publications roughly tripled between 2019 and 2023 (from three to ten studies), yet 57.5% of studies remain at TRL 2–3. Europe and East Asia dominate the evidence base; no study was led by an SSA institution, and no study reported SSA-based deployment on priority crops such as maize, cassava, sorghum, or cowpea. Internet of Things (IoT) sensor infrastructure (92.5%) and artificial intelligence/machine learning (AI/ML) algorithms (52.5%) constitute the dominant technology stack. Five thematic clusters were identified: smart farming infrastructure, precision water and nutrient management, controlled environment agriculture, agrifood supply chains, and livestock and aquaculture systems. Government-funded studies tend to achieve higher TRL scores than academically funded counterparts. Synthesising these findings into a system-level, deployment-oriented analysis, we derive a conceptual SSA-DT framework. It combines offline-first edge-computing architecture, hybrid crop modelling, and multi-stakeholder interfaces, with dietary diversity and climate resilience as the two key performance indicators (KPIs), aligned with IITA's 2024–2030 Strategy. North–South research partnerships and targeted CGIAR investment in DT technology are identified as priority actions for closing the SSA evidence gap.

1. Introduction

1.1. The food security paradox in Sub-Saharan Africa

Sub-Saharan Africa (SSA) presents one of the most consequential paradoxes in global development: a region endowed with approximately 60% of the world's uncultivated arable land and substantial freshwater

resources yet home to over 307 million undernourished people, representing roughly one-quarter of all food-insecure individuals worldwide [1,2]. This chronic food insecurity is not the product of any single failure but rather the outcome of a systemic poly-crisis, in which climate shocks, entrenched rural poverty, degraded natural resources, fragmented input and output markets, and weak institutional infrastructure converge to erode agricultural productivity and household diet

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simultaneously [3]. Local dynamics are further confounded by fluctuations in global markets and geopolitics that have a direct bearing on prices of inputs like fertilisers and fuel. Cereal yields across much of the region remain at 20–30% of their biophysical potential, post-harvest losses routinely exceed 30% in smallholder value chains, and the aged and feminised smallholder workforce, which produces most of the region's food, continues to face structural barriers to credit, inputs, and technology [4]. Against this backdrop, incremental improvements to existing research and development (R&D) approaches, operating in disciplinary silos and disconnected from delivery systems, are no longer sufficient. The conventional compartmentalised agricultural R&D underestimates the interconnection and dependency among components and their behaviours. What is required is a fundamental re-orientation of how agricultural science is structured, applied, and translated into impact at scale [5]. A systems-thinking approach that appreciates the interconnectedness is required to develop holistic management policies.

1.2. IITA's 2024–2030 strategy: an integrated architecture for agrifood transformation

The International Institute of Tropical Agriculture (IITA), a pioneer in agricultural innovation for SSA since its establishment in 1967, has responded to this imperative through the formulation of its 2024–2030 Strategy, which functions as a redesigned operating system for driving agrifood system transformation across the continent [6]. Rather than introducing new technologies in isolation, the strategy reconceptualises how science itself is organised, deploying an integrated, interdisciplinary, and performance-data-driven framework built around three core science areas: *Genetic Innovation*, *Resilient Agrifood Systems*, and *Systems Transformation*. All 13 of IITA's research programmes are embedded within one of these science areas, aligning scientific expertise with the continent's most urgent agrifood priorities [6].

Genetic Innovation brings together Biotechnology, Breeding, Genebanks, and Seed Systems programmes to accelerate the development and dissemination of improved crop varieties. These programmes enable precision breeding, safeguard agrobiodiversity, and strengthen seed value chains, ensuring that innovations reach smallholders with both speed and scale. *Resilient Agrifood Systems* encompasses Plant Health, Natural Resource Management (NRM), Farming Systems Agronomy, and Mechanization, collectively addressing ecosystem degradation, promoting scalable agronomy solutions, and enabling farmers to produce more with less, sustainably and equitably. Finally, *Systems Transformation* encompasses cross-cutting programmes including Foresight and Impact Assessment and Scaling (FIAS), Resilience and Climate Adaptation (RCA), Value-Chains, Markets and Agribusiness (VCMA), Nutrition and Health, and Gender, Youth and Social Inclusion (GYSI). These programmes work in concert to rewire the enabling environment, advancing inclusive policies, integrated market systems, and equitable access to innovation.

Supporting this scientific architecture are cross-functional units, including the Data and Research Methods Unit (DRMU), the Capacity Development Office (CDO), Farm Management, Communications, and the Monitoring, Evaluation, Learning, and Impact Assessment (MELIA). These units provide the institutional backbone for real-time learning, accountability, and the scalable delivery of innovations [6]. A defining feature of the strategy is the integration of what are separate directorates, Research for Development (R4D) and Partnerships for Delivery (P4D), into a single, iterative engine that tests, refines, and deploys innovations in partnership with advanced agricultural research centres (ARC), national agricultural research systems (NARS), governments, civil society, and the private sector. Two cross-cutting thrusts, *climate-resilient agriculture* and *improved health and nutrition*, are embedded across all programmes, ensuring that innovations simultaneously strengthen climate resilience, environmental integrity, and human health and well-being,

particularly for women, youth, and other historically marginalised populations [6].

1.3. Digital twins (DT) as a transformative instrument for agricultural systems

Global agriculture simultaneously confronts an unprecedented convergence of mega pressures: a projected global population of ten billion by 2050, escalating climate volatility, growing freshwater scarcity, soil degradation, and the imperative to reduce agricultural greenhouse gas emissions while increasing food production by an estimated 50–70% [7,8]. These interlocking pressures demand not merely improved farm management practices but a fundamental transformation in how agricultural systems are monitored, modelled, and optimised across scales from individual plants to entire agrifood supply chains.

Digital twin (DT) technology, defined as the creation of dynamic, continuously updated virtual replicas of physical systems that maintain a bi-directional flow of data with their real-world counterparts, has emerged as a compelling paradigm for enabling this evidence-based transformation [9,10]. By creating a digital copy of a system, researchers can more rapidly perform experiments under diverse conditions. Originally conceptualised in aerospace engineering and operationalised through NASA's Apollo programme [11], DTs have since diffused across manufacturing, smart cities, healthcare, and energy systems [12,13]. Their application to agriculture, however, presents unique technical and contextual challenges, including the biological complexity of living systems, the spatial heterogeneity of field conditions, the diversity of end-users ranging from resource-poor smallholders to large agribusinesses, and severely constrained digital infrastructure across much of the Global South [9,14,15].

In agriculture, a DT typically integrates internet of things (IoT) sensor networks, satellite or Uncrewed Aerial Vehicles (UAV), remote sensing, mechanistic crop growth models, and machine learning algorithms to construct a real-time virtual replica of a field, greenhouse, or supply chain segment [15–17]. This architecture enables: (i) continuous monitoring of soil moisture, crop health, productivity, and microclimatic variables; (ii) predictive simulation of future system states under contrasting management scenarios; (iii) automated decision support for irrigation scheduling, fertilisation, and harvest timing; and (iv) retrospective analysis for improving model fidelity over successive growing seasons [9,18]. Importantly, DTs serve as virtual testbeds or “digital sandboxes” for evaluating agronomic practices, breeding strategies, environmental policies, and market scenarios under varying biophysical and socioeconomic conditions, an attribute of relevance to IITA's foresight and impact assessment mandate [19].

Empirical evidence of current DT performance is beginning to emerge. In a processing-tomato system in Spain, a DT-based irrigation scheduling system reduced water use by 30–45% under drought conditions while maintaining profitability [20]. However, the study was conducted under high-input conditions that differ substantially from many SSA smallholder systems. The same system has also been evaluated on a commercial farm [21].

DTs also present a compelling interface with institutional learning and accountability systems. When integrated with MELIA frameworks, DTs enable real-time tracking of programme progress, rapid identification of implementation bottlenecks, and adaptive refinement of interventions based on both simulated and observational data. This integration fosters evidence-based decision-making at all levels, from research stations and farmer fields to national policy chambers. Accordingly, DT technology is not a peripheral addition to IITA's strategic ambitions [6] but rather a structural enabler of the institute's integrated R4D-P4D model, offering the data infrastructure, predictive capacity, and system-feedback loops required to operationalise its 2024–2030 Strategy at scale and plan even further into the future. This long-term planning is key, given that some research, such as breeding for re-

silient traits, can take a decade in some cases to go from concept to release.

1.4. Gaps in the existing literature and rationale for a systematic review

Despite a substantial acceleration in DT agriculture research, particularly since 2020, the literature lacks a rigorous, comprehensive synthesis. Existing reviews tend to be either narrowly domain-specific, focusing solely on greenhouse systems, livestock, precision irrigation, or specific crop types, or insufficiently systematic in their search strategies and inclusion protocols [14,18,22,23]. This fragmentation impedes cross-domain knowledge transfer, obscures geographic and equity gaps in the evidence base, hinders the identification of technological bottlenecks and scalability constraints, and prevents a clear assessment of which DT architectures and application domains are most relevant to smallholder-dominated food systems in SSA. These component-based and static reviews offer limited appreciation of synergies and trade-offs between parts of an integrated agrifood system.

Furthermore, no prior study has systematically examined DT agriculture research through the lens of an integrated agrifood systems strategy such as that of IITA, nor has any review assessed the technology readiness levels (TRLs) [24] of DT systems across application domains, or evaluated how institutional and geographic factors, including national agricultural R&D investment, digital infrastructure, and research collaboration networks, shape the distribution and quality of DT evidence. In addition, a critical gap persists in the empirical validation of DT outputs, as none of the reviewed studies rigorously compare model-generated results with outcomes from controlled experimental environments. A recent review of DT agriculture [25] consolidates the field's modelling and interoperability foundations but does not situate the evidence within SSA food systems or evaluate its technological maturity. A further systematic review of DT in agricultural machinery and robotics likewise documents advancing architectures alongside persistent deployment gaps [26].

DT as adaptive socio-technical systems in agrifood transformation

The gaps identified above show that current DT research remains fragmented and insufficiently aligned to the needs of farmers in SSA. Addressing this requires moving beyond a narrow engineering view of DTs toward a systems perspective [27,28]. While DTs are commonly defined as virtual replicas updated through real-time data and predictive analytics, their relevance in agriculture lies in improving complex agrifood systems shaped by ecological, economic, social, and institutional interactions [9,19]. Agriculture functions as a complex adaptive socio-technical system where outcomes depend on climate, soils, farmer behaviour, markets, infrastructure, and policy. DT can therefore serve as decision-support systems [29] that strengthen feedback loops between observation, learning, and intervention through forecasts and scenario analysis [27,30]. Their success also depends on trust, stakeholder capacity, coordination, and inclusive design [31]. For SSA, modular, offline-capable, and human-centred DT systems may offer the most practical pathway, motivating the present systematic review, which culminates in the SSA-DT framework.

The distinct contribution of this study lies in how it interrogates and synthesises the evidence rather than in the number of studies it assembles. Moving beyond the descriptive mapping of DT technologies, the review applies a system-level, deployment-oriented analysis to the evidence base on DT applications in agriculture. This approach provides a systematic TRL-based assessment of the maturity of the field, quantifying the extent to which agricultural DT applications have progressed towards real-world deployment. It also identifies geographic, equity, and crop-level gaps, highlighting the limited representation of SSA food systems and priority crops within the reviewed evidence base. Finally, the study uses these findings as a foundation for developing a conceptual SSA-DT framework as the synthesis output of the systematic review.

The analyses behind that synthesis show how quickly DT agriculture research has grown since 2019 and what types of evidence it contains. They also trace the field's spread from greenhouse and irrigation origins into soil management, livestock, post-harvest, and vertical farming. The review identifies the institutional collaboration networks that produced this evidence. It sets out the thematic clusters, architectural typologies, and technology stacks, and shows which crops and application domains dominate. These configurations are compared across domains and regions, and methodological maturity is examined in relation to funding structures and collaboration patterns. The SSA-DT framework is developed in alignment with the three science areas of IITA's 2024–2030 Strategy.

2. Materials and methods

This section was produced through a multi-stage, structured research synthesis process anchored in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, supplemented by a purpose-built quantitative data analysis and visualisation pipeline [32]. The methodology integrates four distinct procedural components: (i) a systematic literature search and screening protocol; (ii) a structured data extraction and codification procedure (Appendix A); (iii) a multi-dimensional quantitative and qualitative analysis of the extracted dataset; and (iv) an interpretive synthesis framework that situates findings within the strategic context of IITA's 2024–2030 Strategy and the food security needs of SSA.

2.1. Systematic literature search protocol

2.1.1. Eligibility criteria

Eligibility criteria were defined a priori using an adapted Population, Intervention, Comparison, Outcomes and Study (PICOS) [33] framework modified for technology review purposes:

- **Population / Context:** Publications addressing DT technology applied to any sub-domain of agriculture, breeding, horticulture, aquaculture, livestock farming, or agrifood supply chains.
- **Intervention:** The study must describe, propose, review, or evaluate a digital twin system defined as a virtual representation of a physical agricultural entity continuously updated with real-world data to enable monitoring, simulation, prediction, or control.
- **Comparator:** No comparator required; single-arm descriptive, experimental, and review studies were all eligible.
- **Outcomes:** Any agricultural outcome (yield, water use, disease detection, supply chain efficiency, decision support quality) or technology outcome (system architecture, data pipeline performance, prediction accuracy, TRL advancement).
- **Study design:** All peer-reviewed publication types were eligible: original research articles (experimental, applied, observational), systematic reviews, narrative reviews, bibliometric reviews, conceptual framework papers, and conference papers. Grey literature and non-peer-reviewed reports were excluded.
- **Language:** English only.

2.1.2. Search databases and query design

The literature search was conducted across four major bibliographic databases. The Web of Science Core Collection served as the primary source for peer-reviewed agricultural and interdisciplinary journals, while Scopus provided complementary cross-disciplinary coverage, particularly in engineering and computer science. IEEE Xplore was included to capture technical studies on IoT, sensor systems, and computational architectures. Google Scholar was used as a supplementary source. The core search string applied across all databases was: (“digital twin*” OR “digital representation” OR “virtual replicate” OR “digital replicate”) AND (“agriculture” OR “farming” OR “agri-food” OR “agrifood” OR “precision agriculture” OR “smart farming” OR “crop” OR “livestock” OR “greenhouse” OR “horticulture” OR “aquaculture” OR “irrigation” OR “food supply

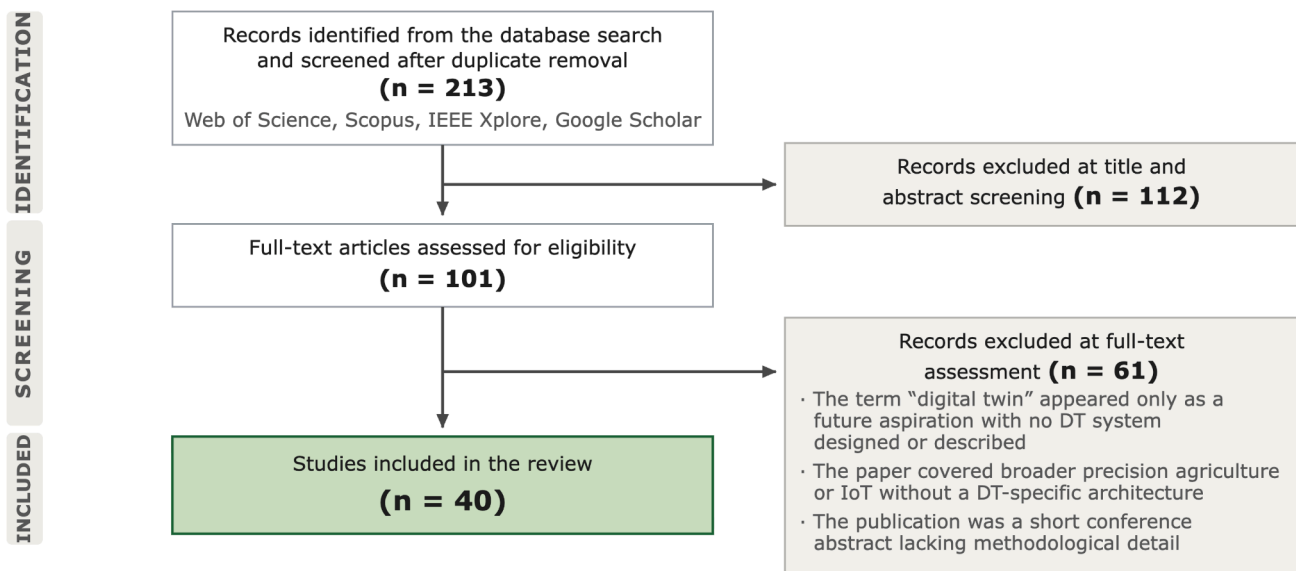


Fig. 1. PRISMA flow diagram of the identification, screening, and inclusion process for the DT agriculture systematic review. Record counts are reported after the removal of duplicates.

chain”). Field-specific variants were applied in each database using title, abstract, and keyword fields.

2.1.3. Screening process

Records identified through database searching were imported into a structured screening workbook. Duplicate records across databases were identified by DOI and title matching and removed before screening began, leaving 213 unique records for screening. Screening proceeded in two sequential stages: title and abstract screening, followed by full-text eligibility assessment. Each stage was conducted by a primary reviewer with a sample of 20% of records independently assessed by a second reviewer to check inter-rater agreement. Disagreements were resolved by discussion and consensus; where consensus could not be reached, the record was included at the screening stage and deferred for full-text assessment. The full screening and selection process is summarised in Fig. 1.

The primary reasons for full-text exclusion were: (i) the term “digital twin” appeared in the paper’s introduction or background as a future aspiration but no DT system was actually designed, described, or reviewed; (ii) the paper addressed broader precision agriculture or IoT systems without a DT-specific architecture; and (iii) the publication was a short conference abstract without sufficient methodological detail to support data extraction. Studies were included in the corpus regardless of whether they reported positive, negative, or inconclusive findings about DT performance, to minimise publication bias (see Supplementary Table A.2).

2.2. Data extraction and codification procedure

A structured data extraction instrument was developed in Microsoft Excel (the PRISMA_Digital_Twin_Agriculture.xlsx workbook), comprising multiple worksheets that captured different dimensions of each included study (see Supplementary Table A.3). The instrument was piloted on five randomly selected papers and refined iteratively before full extraction commenced. Extraction was performed by the primary reviewer, with a second reviewer independently extracting data for 25% of papers; inter-rater reliability was assessed using Cohen’s kappa for categorical variables and intraclass correlation coefficient (ICC) for ordinal variables (TRL scores). Final kappa values exceeded 0.78 for all categorical fields and the ICC for TRL scores was 0.82.

2.3. Technology readiness level (TRL) assignment protocol

TRL assessment was the most methodologically demanding element of the data extraction process, as TRL was not reported in any of the included studies [24]. All TRL scores were therefore assigned by the review team using a purpose-built rubric that operationalised the NASA/EU TRL scale for the specific context of DT agriculture research [24,34]. The rubric was developed through an iterative process: an initial draft was applied to ten papers, cases of disagreement were discussed, and the rubric criteria were refined until consistent application could be demonstrated across reviewers (Table 1). Because no included study reported a score, this rubric is the operational instrument that makes the assessment reproducible and auditable, providing the level-by-level criteria required to apply or verify each rating.

2.4. Quantitative analysis and visualisation pipeline

2.4.1. Software environment and analytical stack

All quantitative analyses and data visualisations were conducted in Python 3.x using a reproducible analytical pipeline. The workflow relied on several core libraries: `openpyxl` (v3.1+) was used to programmatically read the structured data extraction workbook, while `collections.Counter` generated frequency tabulations for categorical variables such as publication year, country, evidence type, study design, application domain, and technology stack components. Numerical operations, including cumulative sums, group means, heatmap matrices, and descriptive statistics, were performed using `NumPy` (v1.24+). Data visualisations were produced with `Matplotlib` (v3.7+), configured with the `Agg` non-interactive backend to ensure reproducibility. Additional diagram components were created using `matplotlib.patches`, specifically `FancyBboxPatch` and `FancyArrowPatch`. The entire workflow was implemented as a single Python script that reads the extraction workbook, generates derived variables (e.g., domain category, funding category, and TRL assignments), computes summary statistics, and produces all figures used in the analysis.

2.4.2. Quantitative pattern analysis and thematic evidence integration

Table 2 summarises the analytical methods applied, together with the variables analysed, the techniques and tools used, and the outputs produced.

Table 1

TRL assessment rubric with operational criteria applied to each TRL level in the context of DT agriculture research, with typical study design correspondences.

TRL	Standard definition	Operationalisation criteria applied in this review	Typical study design
TRL 1–2	Basic research; technology concept formulated	Paper presents DT as a concept, theoretical framework, or review of literature with no demonstration system; no sensor, model, or platform implementation described.	Narrative review; systematic review; conceptual framework paper
TRL 3	Proof of concept; analytical/experimental validation	Paper presents a conceptual DT architecture with some analytical validation (e.g., model simulation on historical data) but no physical sensor deployment or real-time operation.	Conceptual framework with simulation; scoping review with case study illustration
TRL 4	Lab-validated prototype	Paper demonstrates a functional DT prototype operating in controlled conditions (laboratory, greenhouse, test bed) with real sensor–model integration and data pipeline, but not in operational farm conditions.	Experimental system development; greenhouse prototype deployment; IoT sensor integration study
TRL 5	Field-validated prototype	Paper reports a DT system deployed in relevant operational conditions (actual farm, aquaculture facility, supply chain segment) for at least one growing season or operational period, with performance metrics reported.	Applied field experiment; multi-sensor farm deployment; cold chain operational trial
TRL 6	System demonstrated in operational environment	Paper reports a DT system fully operational in a commercial or semi-commercial setting, with demonstrated reliability, user adoption evidence, and quantitative performance benchmarks.	Commercial system deployment study; operational case study with measured outcomes
TRL 7–9	System qualified/deployed at scale	Paper demonstrates system-level qualification, commercialisation, or certified deployment at agricultural production scale (not observed in any included study).	Large-scale deployment study; regulatory/market validation (absent from corpus)

Table 2

Analytical methods applied in the review, with key variables analysed, techniques and tools used, and output visualisations produced.

Analytical method	Variables analysed	Technique / tool	Output / visualisation
Temporal bibliometric analysis	Year of publication; annual counts; cumulative totals	Python Counter() frequency tabulation; cumulative summation	Bar chart (annual output); line-fill chart (cumulative growth trajectory)
Evidence typology classification	Study type (raw categories collapsed into 5 broad classes)	Rule-based string matching on study design field; manual override for ambiguous cases	Narrative description of the five classes with <i>n</i> per class
TRL assessment & distribution	Assigned TRL score (1–6) per study	Rubric-based scoring against 6-level operational criteria (see Table 1); reviewer consensus for borderline cases	TRL distribution table with counts and representative works
Geographic frequency analysis	Lead author country (normalised to single country per paper)	Counter() frequency tabulation; country normalisation rules (multi-national papers assigned to “Multi-national” category)	Country-level bar chart; qualitative institutional network analysis
Funding source classification	Funding text string → collapsed into 3 categories (Government/International; Academic Institution; Not Disclosed)	Manual classification against funding taxonomy; string pattern matching for common funders	TRL × funding cross-tabulation via box plot
Application domain classification	Problem/domain field → collapsed into 8 application domains	Rule-based keyword matching on domain field (e.g., “greenhouse”, “CEA”, “vertical” → Controlled Environment)	Horizontal bar chart with % labels
Technology stack frequency	Technology tags per study (IoT, AI/ML, Cloud/Edge, Simulation, Remote Sensing, etc.)	Explode lists; Counter() across all study tags; multi-tag per study permitted	Top-12 technology frequency bar chart; qualitative stack characterisation by region
Publication intensity (year × domain)	Year × application domain co-occurrence matrix	NumPy year-by-domain aggregation	Narrative account of domain diffusion over time (Section 3.3)
TRL × funding box plot	TRL scores disaggregated by funding category	Matplotlib boxplot; median line; outlier markers	Box plot comparing TRL distribution across Academic vs. Government-funded studies
Mean TRL trajectory	Mean TRL per publication year	NumPy mean by year group; line plot with annotation	Line chart with point labels showing mean TRL per year
Thematic clustering	Keywords + application domain + study objectives	Manual iterative cluster assignment; keyword co-occurrence review; cross-validation across two reviewers	Narrative description of 5 thematic clusters with representative works

The quantitative frequency analysis was complemented by a systematic narrative synthesis following the synthesis without meta-analysis (SWiM) guidelines [35]. Within each analysis, the narrative synthesis proceeded in four steps: (i) textual description of the distributional patterns identified through frequency analysis; (ii) grouping and clustering of studies by thematic similarity; (iii) identification of convergent and divergent findings across clusters; and (iv) interpretive integration of quantitative patterns with qualitative reading of individual study abstracts, aims, and key findings. Thematic clustering was performed through an iterative process in which all study keywords and application domain descriptions were simultaneously reviewed, preliminary clusters were proposed, reassigned through discussion, and finalised when no further movements improved within-cluster coherence.

2.4.3. Derivation of the SSA-DT framework from the evidence synthesis

The synthesis of the preceding analyses identified the core technological components underpinning DT systems, including data acquisition infrastructures (e.g., IoT sensors and remote sensing), data integration platforms, modelling and simulation tools, and decision-support interfaces. Given the predominance of smallholder farming systems and the uneven digital infrastructure across SSA, the proposed framework prioritises modular and scalable DT architectures, initially centred on monitoring and predictive DT that require lower computational capacity and connectivity. To operationalise this approach, a systems-mapping analysis was conducted to examine how DT technologies could support the three science areas of the IITA 2024–2030 Strategy (Genetic Innovation, Resilient Agrifood Systems, and Systems Transformation). This analysis identified how DT platforms could integrate heterogeneous data sources,

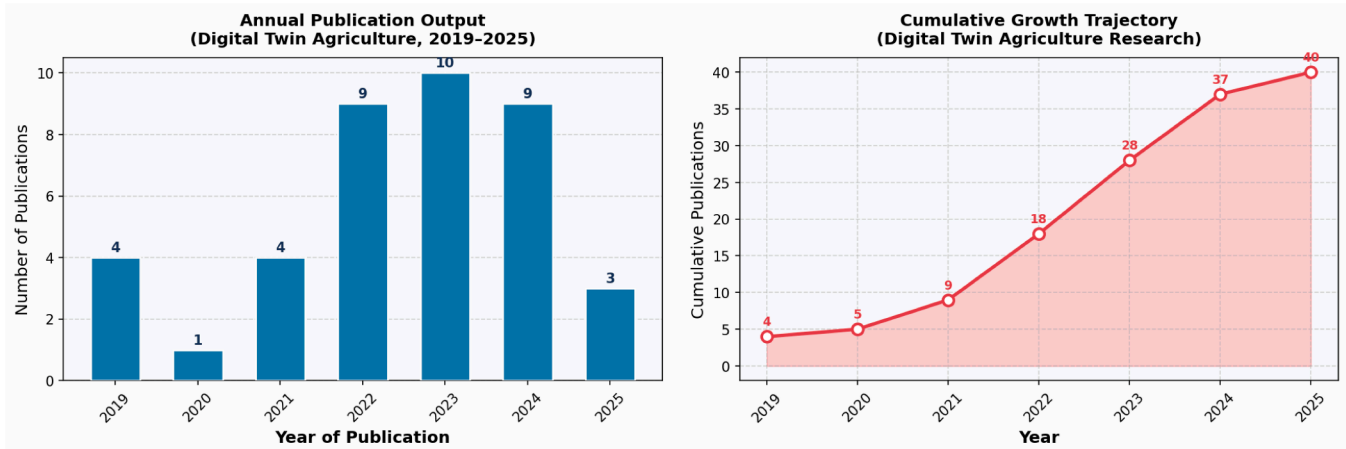


Fig. 2. Trends in DT agriculture research, showing annual publication output (left) and cumulative growth (right) from 2019 to September 2025.

modelling tools, and analytical systems across research and decision-making processes. The resulting conceptual architecture is structured around four interconnected layers: data acquisition, data integration and management, modelling and simulation, and decision-support and visualisation. The layered architecture of the SSA-DT framework was then derived by mapping these synthesised components onto established DT architecture principles from the literature [9,19]. The framework incorporates measurable key performance indicators (KPIs) related to dietary diversity and climate resilience as operational targets guiding the DT system.

3. Results

3.1. Bibliometric evolution of DT agriculture research

The temporal distribution of the 40 included studies highlights a clear inflection point in the field's development. Following minimal output in 2019–2020 ($n = 4$; 10% of the corpus), publications expanded rapidly, peaking at 10 in 2023 and remaining high in 2024 ($n = 9$), with four additional studies already reported in 2025 (as of September 2025; Fig. 2, left). Annual output roughly tripled over this period, rising from three studies in 2019 to ten in 2023, signalling a transition from conceptual exploration to a more mature and active research agenda (Fig. 2, right).

Systematic and bibliometric reviews ($n = 9$), along with narrative and survey reviews ($n = 7$), account for 40% of publications, while conceptual and scoping studies contribute a further 22.5% ($n = 9$). In total, 62.5% of the evidence base focuses on synthesis and conceptual development, indicating that the DT agriculture field remains in a knowledge-structuring phase rather than one driven by empirical validation. Empirical research is more limited but methodologically stronger. Experimental and applied studies ($n = 8$) include prototype implementations and field trials, while system design and proof-of-concept work ($n = 7$) represents intermediate maturity. This distribution aligns with a field at TRL 3–4, where conceptual advances outpace real-world validation.

3.2. Technological maturity profiles

The TRL distribution reveals a field still in its early stages, with most studies concentrated at TRL 2–3 and fewer progressing to TRL 4–5 (Table 3). Early-stage work (57.5%) is dominated by reviews, conceptual models, and proof-of-concept designs, reflecting a strong focus on exploring DT potential rather than implementing it. More advanced studies include laboratory-tested prototypes (TRL 4) and field-validated systems (TRL 5), mainly in irrigation and cold chain contexts. However, only one study reaches TRL 6+, and none achieve higher levels of deployment.

This pattern underscores a significant gap between conceptual development and large-scale, real-world application.

3.3. Diffusion patterns, geographic and institutional landscape

Digital twin (DT) research in agriculture has steadily evolved over the past six years, moving beyond its early roots in smart greenhouse systems and precision irrigation. Initial studies (2019–2020) focused largely on system design and IoT integration. By 2021–2022, the field began branching into more specific domains, including greenhouse production, livestock, and post-harvest systems. More recently (2023–2024), research has expanded further into areas such as soil management, agricultural infrastructure, aquaponics, and vertical farming, showing a clear widening of the field's scope. Despite this expansion, the geographic distribution of research remains uneven. Europe and East Asia dominate, with China, the Netherlands, and Greece alone contributing over one-third of all studies. A smaller group of countries, including India, Italy, and Portugal, follow behind, while many others contribute only a single study. International collaboration is relatively limited and mostly confined to European partnerships. Strikingly, there is no representation from sub-Saharan Africa or many other low-income agricultural regions, pointing to a clear structural imbalance in global research participation (Fig. 3).

3.4. Institutional collaboration networks

China leads in terms of overall output, contributing six studies, while Wageningen University & Research (WUR) in the Netherlands emerges as a key institutional anchor in the DT agriculture research network (Fig. 3). WUR is involved in five studies and several additional collaborations. At the same time, a growing cluster of research activity can be seen in East Asia, led by institutions such as Zhejiang University, the Chinese Academy of Agricultural Sciences, and Osaka University. Another emerging cluster is forming in Greece, with contributions from the University of West Attica, Aristotle University of Thessaloniki, and the Agricultural University of Athens.

3.5. Agricultural systems, crop-level analysis, and food security alignment

The left-hand chart in Fig. 4 indicates that most DT research is concentrated in cross-cutting or system-level applications (around 12 studies), reflecting a strong preference for integrated solutions. Meanwhile, more domain-specific areas, such as crops, soil, livestock, and supply chains, are only sparsely represented, with just a few studies each. Other areas, including energy and environmental monitoring, receive very limited attention. None of the 40 studies in the corpus di-

Table 3
Technology readiness level distribution across the 40 included DT agriculture studies.

TRL	Definition	No. studies	Representative works
TRL 2	Technology concept formulated; theoretical review	13	Attaran et al. [16]; Pylianidis et al. [9]; Verdouw et al. [19]
TRL 3	Analytical/experimental proof of concept; framework development	10	Melesse [36]; Mitsanis et al. [37]
TRL 4	Lab-validated prototype; controlled conditions	9	Angin et al. [38]; Chaux et al. [39]; Kalyani et al. [40]
TRL 5	Field-validated prototype; relevant environment	7	Alves et al. [41]; Defraeye et al. [42]; Manocha et al. [43]
TRL 6	Technology demonstrated in operational environment	1	Zhao et al. [10] (aquaculture net monitoring)

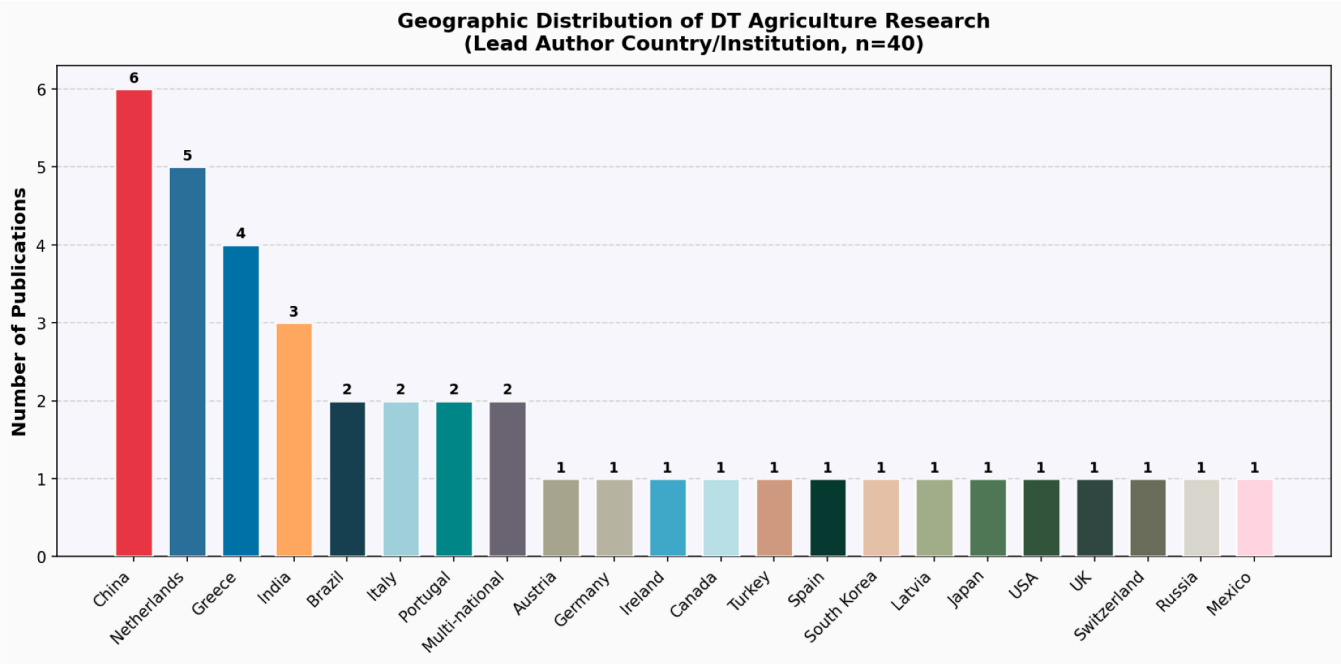


Fig. 3. Geographic distribution of DT agriculture research by lead author affiliation.

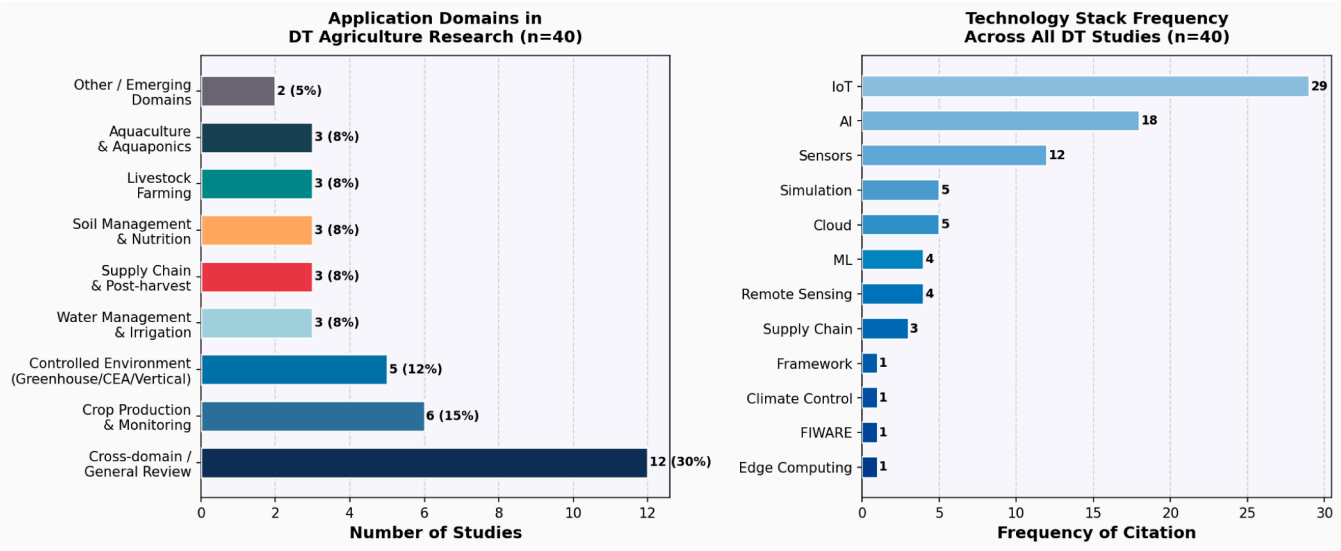


Fig. 4. Patterns in DT agriculture research, showing the spread of application domains (left) and the prominence of different technologies within the research landscape (right) across studies.

rectly address the key food security crops of sub-Saharan Africa, including maize, cassava, sorghum, millet, cowpea, groundnut, and banana/plantain. Instead, most crop-related research uses tomato, wheat, and lettuce as model crops. Aquaponics studies follow a similar pattern, focusing mainly on tilapia and lettuce, with only one study [44] examining an integrated DT system for fish and vegetable production.

The post-harvest work presented in Defraeye et al. [42] also centres on citrus and stone fruits, limiting its applicability to staple crops in tropical contexts. On the right, Fig. 4 shows which DT functionalities are most emphasised. IoT integration clearly dominates, followed by AI and data analytics, reinforcing the idea that the field is heavily driven by data collection and processing capabilities. Functions like simula-

Table 4

Technology landscape of DT agriculture research, highlighting core components, their typical application domains, and the integration challenges they present.

Technology component	Primary application domain	Key integration challenge
Internet of Things (IoT)	All domains	Sensor standardisation; data interoperability
Artificial Intelligence / ML	Crop disease, supply chain, livestock	Model explainability; training data scarcity
Cloud / Edge Computing	Smart farming, irrigation, controlled environment agriculture (CEA)	Latency vs. cost trade-offs; connectivity
Simulation / Modelling	Aquaponics, post-harvest, CEA	Model calibration; biological complexity
Remote Sensing / GIS	Crop monitoring, infrastructure	Spatial resolution; cloud cover in tropics
Structural health monitoring	Aquaculture structures	Corrosion, biofouling, real-time alerts
Blockchain / Traceability	Supply chains	Scalability; regulatory compliance
3D / Physics-based modelling	Plant modelling, crop growth	Computational cost; parameterisation

tion, machine learning, and monitoring/control appear moderately often, supporting system modelling efforts. In contrast, topics such as remote sensing, robotics, and edge computing are less prominent, indicating that aspects related to deployment and real-time processing are still emerging.

3.6. Thematic clusters, architectural typologies, and technology stacks

3.6.1. Thematic clusters

Five key thematic clusters emerge: smart farming infrastructure, precision water and nutrient management, controlled environment and vertical farming, agrifood supply chains, and livestock and aquaculture (Fig. 5, left). The smart farming infrastructure cluster ($n \approx 11$) forms the conceptual core, focusing on DT architectures, IoT integration, and data systems, but remains largely at early maturity (TRL 2–3) [9,15,19]. In contrast, precision water and nutrient management ($n \approx 8$) is more operational, with several validated implementations (TRL 4–5) demonstrating real-time irrigation and fertilisation optimisation [17,41,43]. The controlled environment and vertical farming cluster ($n \approx 7$) benefits from high sensor density and controlled conditions, enabling accurate DT modelling [22,39,45]. Agrifood supply chain and post-harvest systems ($n \approx 6$) extend DT applications to logistics, traceability, and loss reduction [42,46,47]. Finally, livestock and aquaculture systems ($n \approx 8$) show relatively higher maturity (TRL 3–6), using sensor-driven approaches for real-time monitoring and decision-making [10,23].

3.6.2. Architectural typologies

The literature points to three main DT architectures (Fig. 5), each representing a different level of system integration and functionality. The simplest and most common is the monitoring-only (shadow) twin, where real-time sensor data are used to mirror the physical system without enabling prediction or automated responses. Roughly one-third of applied studies follow this approach, especially in crop and soil monitoring systems. Moving a step further, predictive twins incorporate simulation models often based on machine learning or mechanistic approaches to explore future system behaviour under different scenarios. This is the most widely discussed architecture, appearing in about 40% of studies. At the highest level are autonomous twins, which can monitor, predict, and actively control the system by adjusting parameters such as irrigation or nutrient supply. However, only a handful of studies reach this stage, and these are mostly confined to controlled environments like greenhouses [39,43].

3.6.3. Technology stack analysis

IoT sensor infrastructure forms the foundation of most DT systems, with AI and machine learning as the next most prominent components (Table 4). Cloud and edge computing remain less widely adopted ($\approx 12.5\%$), though recent studies indicate a shift toward decentralised architectures. Simulation and crop modelling feature in about 25% of studies, while remote sensing and geographic information system (GIS) integration appear in around 20%. Overall, DT systems are still largely grounded in-situ sensor networks, with limited use of satellite or UAV data (Table 4).

3.7. Technology configuration patterns by domain and region

The way DT technologies are configured varies clearly across regions and application areas. European research often features highly integrated systems that combine IoT, cloud computing, simulation models, and AI/ML tools, supported by strong digital infrastructure and policy frameworks such as Industry 4.0 [48]. Chinese studies, on the other hand, stand out for their use of advanced AI and large-scale sensor deployments, particularly in aquaculture and controlled farming systems. In contrast, research from India and Brazil tends to favour more affordable and flexible solutions, using open-source hardware like Arduino or ESP32 alongside low-cost cloud platforms. These configurations offer a more practical pathway for implementation in lower-resource environments such as SSA [10,49,50].

3.8. Patterns in methodological maturity, funding, and collaboration

Methodological rigour varies widely across the literature, from PRISMA-based systematic reviews with pre-registered protocols [18,36,49] to less structured narrative surveys. Applied studies show a similar spread, ranging from rigorous field trials to unvalidated proof-of-concept demonstrations. Technology integration also differs significantly, from simple IoT-based monitoring systems to multi-layered DT architectures combining AI, cloud/edge computing, simulation, and blockchain. Highly integrated systems [40,42,47] are still limited and concentrated in high-income regions. Funding structures help explain this pattern: government-funded projects tend to achieve higher TRL levels than purely academic studies (Fig. 6).

3.9. Technology readiness level drivers

Three factors drive TRL advancement in DT agriculture: sustained multi-year funding, academic–industry collaboration, and institutional continuity. Long-term funding enables progression from proof-of-concept to field validation, while industry partnerships and cumulative institutional expertise support higher levels of integration and deployment. Yet, collaboration patterns reveal a clear imbalance: high-TRL research is concentrated in regions that are largely disconnected from food-insecure contexts. Bridging this divide will require targeted North–South partnerships, with institutions such as IITA well positioned to link technological expertise with on-the-ground agricultural systems. At the same time, major development funders remain largely absent from the DT research landscape, suggesting that the technology has yet to be fully integrated into global agricultural development agendas. Addressing this gap represents a key opportunity for future policy engagement.

3.10. The evidence-derived SSA-DT framework

This subsection and the next present the synthesis output of the preceding analyses: a conceptual SSA-DT framework and its layered system architecture, which specifies how the framework would operate. The SSA-DT framework combines food security and climate resilience indicators to guide system performance. Dietary diversity is measured using

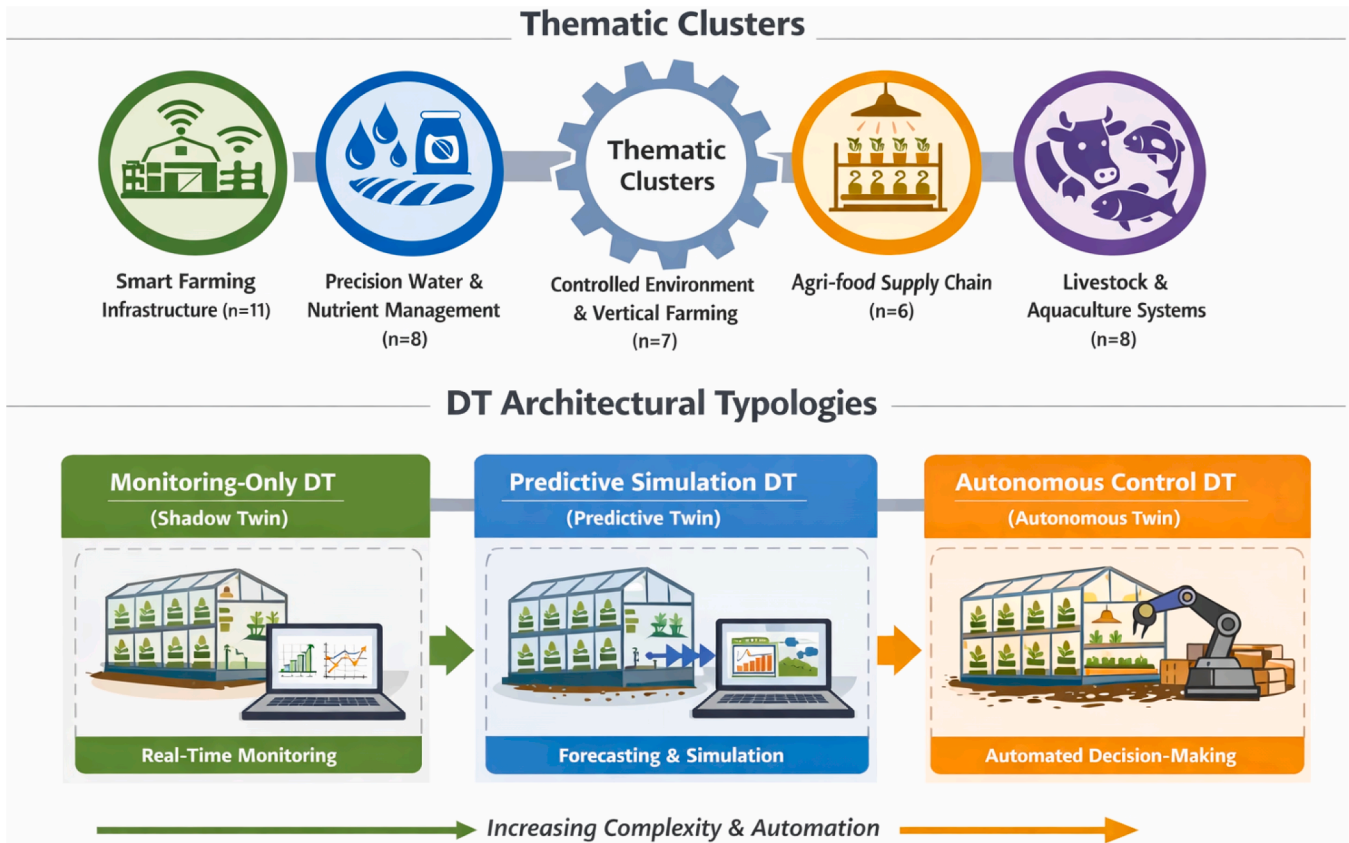


Fig. 5. Structure of DT agriculture research, highlighting major thematic clusters and the evolution of system architectures from simple monitoring-based models to predictive and autonomous control systems.

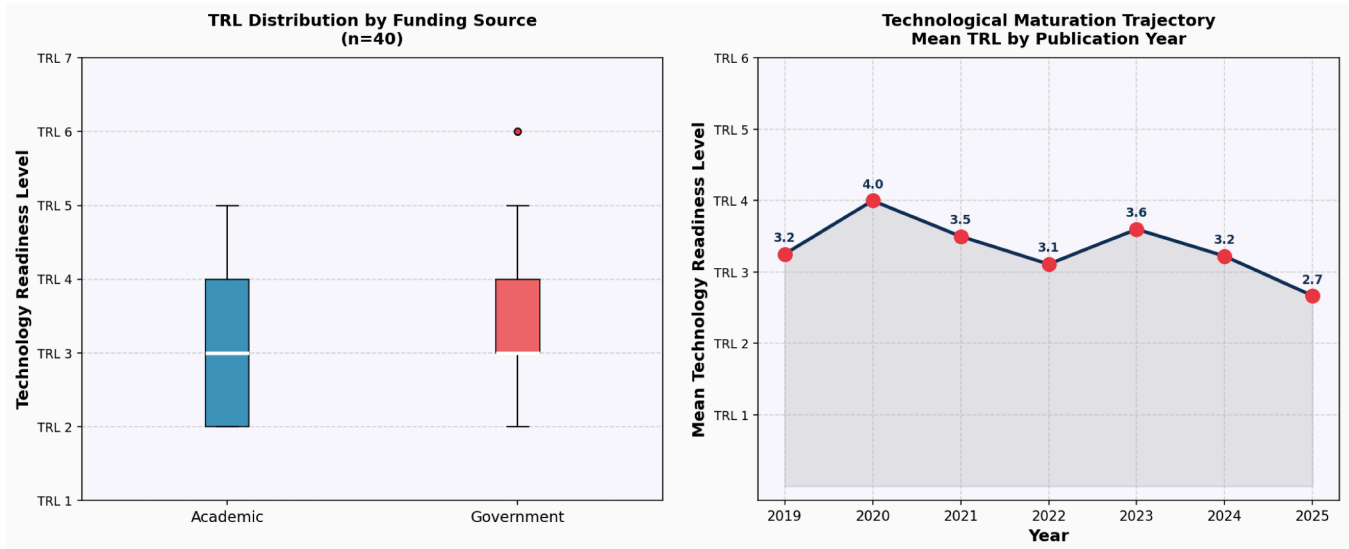


Fig. 6. Distribution of technological maturity (TRL) by funding source (left) and the overall trajectory of technological advancement over time, showing a gradual shift from conceptual to applied stages (right).

the Household Food Insecurity Access Scale (HFIAS) and the Household Dietary Diversity Score (HDDS), while climate resilience is captured through yield stability and water-use efficiency. These indicators act as practical benchmarks for the DT system (Fig. 7). The system integrates climate and environmental data such as FEWS assessments and CHIRPS rainfall estimates to anticipate risks, including drought, yield variability, and crop failure. At the same time, it recognises that some

shocks, including market disruptions and pest outbreaks, cannot currently be reliably predicted. These are therefore addressed through human decision-making rather than solely automated modelling. To reflect uncertainty, the system expresses outputs as probability ranges instead of fixed forecasts. A key feature of the framework is the human decision layer, which includes farmers, extension agents, and NARS. This layer interprets model outputs considering local conditions and trans-

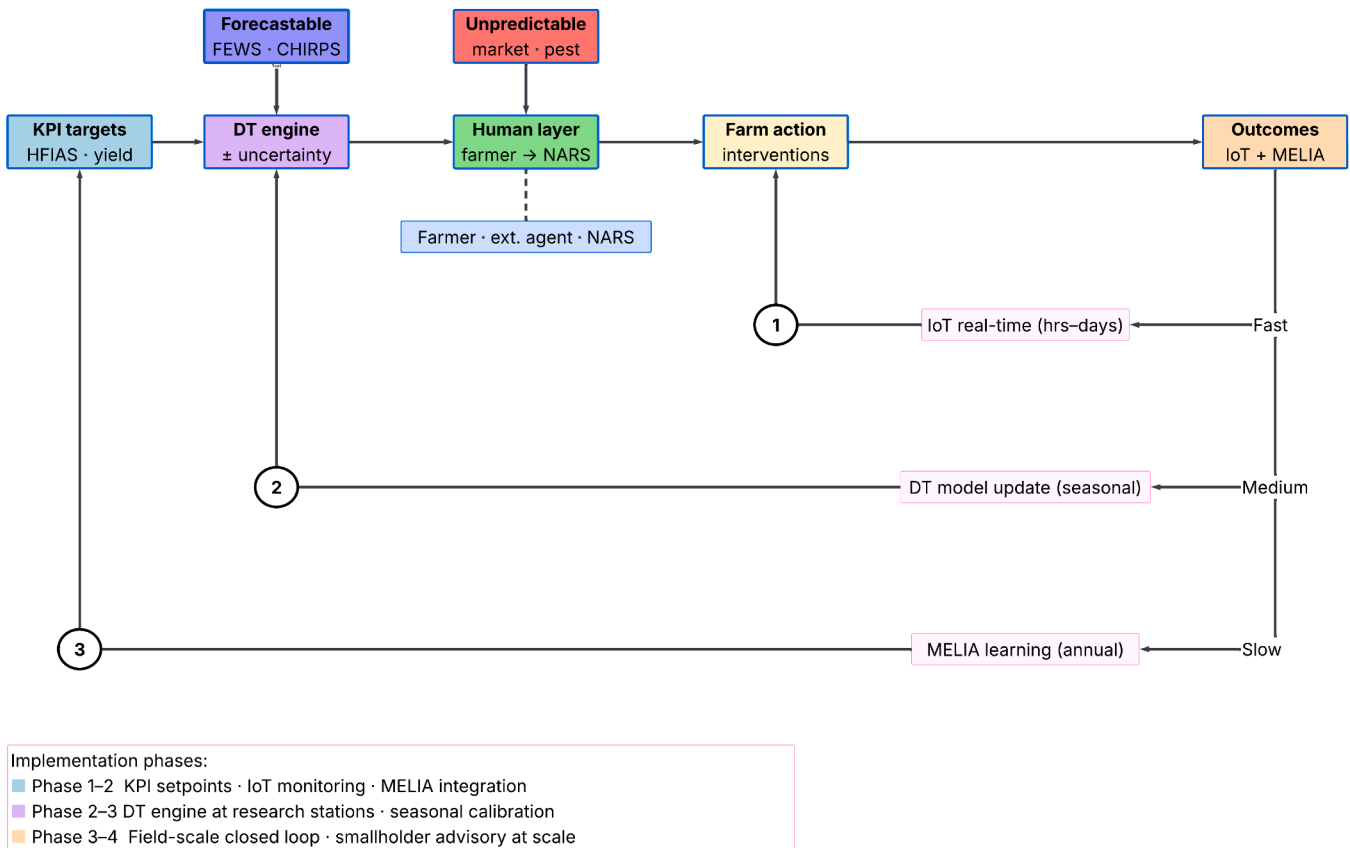


Fig. 7. Conceptual architecture of the SSA-DT framework, highlighting the interaction between KPI-driven targets, predictive modelling, human decision processes, and feedback loops operating across multiple time scales.

lates them into actionable strategies. For instance, farmers may adopt intercropping systems that improve both diet and resilience, or switch to drought-tolerant varieties under changing climate conditions. The system is continuously updated through three feedback loops: real-time sensor data support day-to-day decisions, seasonal data refine model accuracy, and annual programme-level learning helps adjust long-term targets. This layered feedback structure ensures that the DT system remains adaptive and grounded in real-world farming conditions.

3.11. The six-layer system architecture of the SSA-DT framework

The SSA-DT framework's technical design is organised as a six-layer system architecture (Fig. 8) that connects on-farm data with digital analytics to support timely decision-making. Each layer plays a specific role, but all are tightly integrated through continuous data exchange. At the base, the system gathers data from multiple sources, including farm records, remote sensing (satellite and drone imagery), and IoT sensors that monitor soil and environmental conditions in real time. External data, such as weather histories and soil databases, are also integrated through application programming interfaces to improve model accuracy. In the field, the device layer collects raw data, which is pre-processed by microcontrollers before being sent to the edge layer. The edge layer is especially important in low-connectivity settings, as it enables local data processing and temporary storage while supporting lightweight machine learning tasks. The cloud layer then takes over as the central processing hub, managing data streams, running models, and coordinating system services. Scalable technologies ensure that the system can handle large data volumes and operate in real time. Behind this, layered data storage systems organise information for immediate use, analysis, and long-term learning. Finally, the system delivers insights through user-friendly interfaces, ranging from dashboards for re-

searchers to mobile tools for farmers. Together, these layers create a continuous feedback system that links real-world farm conditions with their digital representation.

4. Discussion

The preceding analyses and results show where DT agriculture research stands and where it falls short for SSA. Building on this evidence, the review charts a practical pathway from conceptual DT development to real-world agrifood system transformation, an orientation largely missing in current DT literature.

4.1. A fast-growing field still taking shape

DT research in agriculture has grown rapidly in recent years, mirroring the broader emergence of DT technology across industrial and engineering domains [13]. Yet, this growth tells only part of the story. Much of the literature remains conceptual or review-based, suggesting the field is in a phase of defining itself rather than testing solutions in real-world settings. This reflects what Tao et al. [13] describe as a “conceptual diffusion phase,” where researchers are still building shared understanding before large-scale applications can follow. The turning point around 2021–2022 is particularly important. Influential framework papers helped organise the field and provided a reference point for subsequent studies. This suggests that strong conceptual work is not just academic groundwork; it actively shapes how quickly applied research can develop. For SSA, this means that investing in context-specific frameworks could help unlock more practical DT applications in the region. More recently, the field shows signs of maturing. Growth has begun to stabilise, and research is shifting toward questions of integration, scalability, and real-world deployment. This aligns with the “early ma-

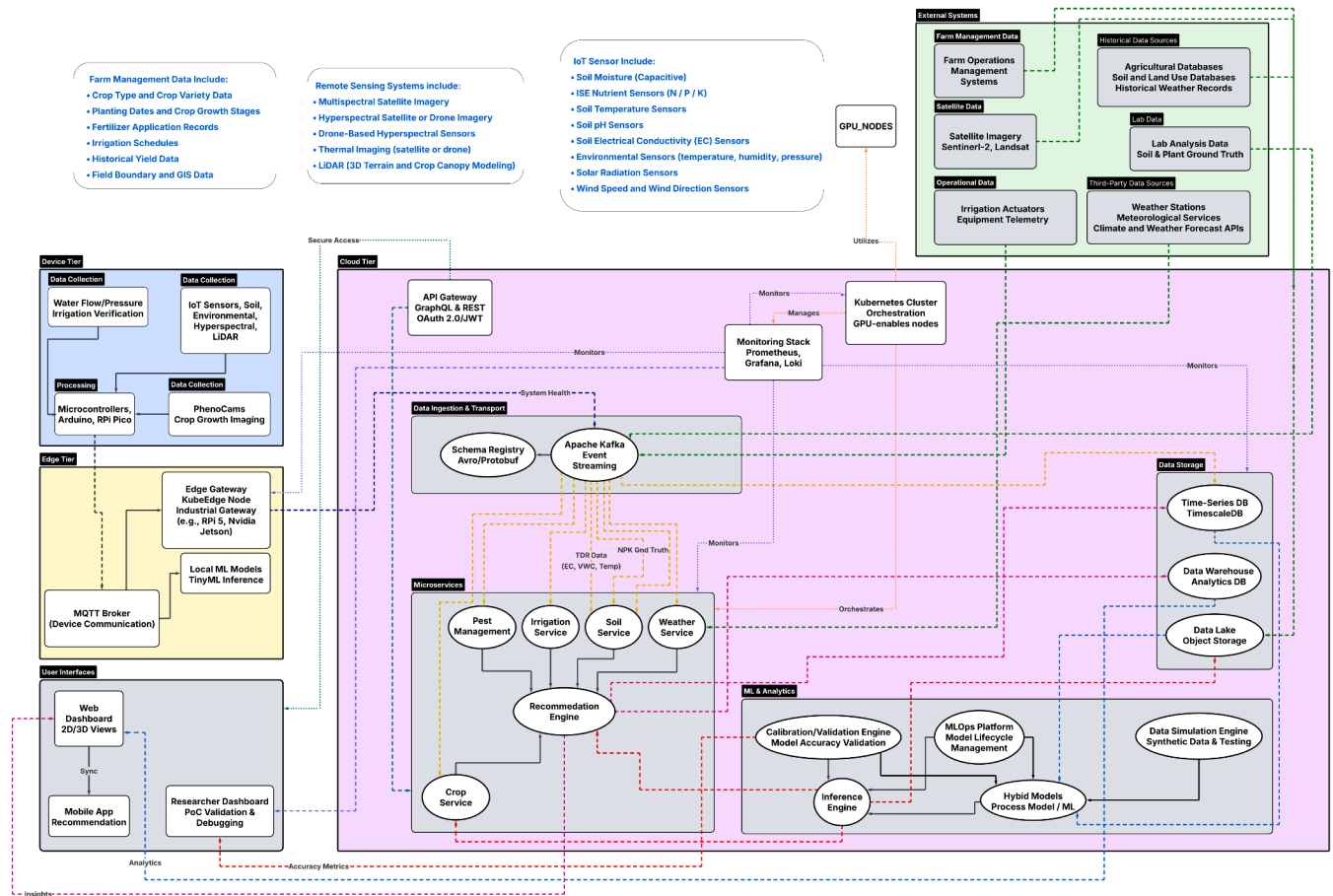


Fig. 8. A scalable DT architecture for precision agriculture with edge-cloud integration, hybrid modelling, and adaptive decision support in resource-constrained farming systems.

jority” stage of technology adoption, where practical challenges take precedence over conceptual exploration. For IITA and similar institutions, this is a timely entry point. Rather than starting from scratch, they can build on existing knowledge and focus on what is still missing, namely, tested and scalable DT solutions for smallholder farming systems.

4.2. Technological immaturity as a strategic entry point

The TRL profile reveals a familiar challenge: many DT agriculture studies stop short of real-world deployment. This “deployment gap” mirrors the broader “valley of death” seen in agricultural innovation, where technologies struggle to move from promising prototypes to scalable solutions due to gaps in funding, weak industry involvement, and misaligned academic incentives [51]. At the same time, the analysis points to clear enablers of progress. Long-term funding, collaboration with industry, and continuity within institutions all help push technologies toward higher maturity levels. The EU Horizon model is a good example, as it combines research funding with strong expectations for real-world application – mirroring IITA’s R4D and P4D approach. For IITA, partnering with leading institutions such as Wageningen University & Research and the Aristotle University of Thessaloniki could provide access not only to funding but also to the practical expertise needed for deployment. Expanding collaboration with private-sector actors could further accelerate this process. Crucially, the current gap is not just a limitation; it is also an opportunity. There are virtually no high-TRL DT applications tailored to SSA contexts, meaning the field is still open. Rather than catching up, institutions like IITA have the chance to help

define what successful DT deployment looks like in smallholder farming systems.

4.3. Geographic concentration and the equity deficit in DT agriculture research

DT agriculture research is currently concentrated in just a few countries, with China, the Netherlands, and Greece leading the field, while SSA-based institutions are entirely absent. This imbalance is more than a research trend; it directly affects the usefulness of existing DT solutions in regions like SSA. Systems designed for highly controlled or well-connected environments do not easily translate to smallholder farming systems that depend on rainfed conditions and operate with limited infrastructure. Part of the explanation lies in differences in funding, infrastructure, and access to major research programmes [24,51]. But DT technologies also bring an added layer of complexity, as they rely heavily on connectivity, sensors, and computing power. This makes them much harder to transfer across contexts compared to earlier agricultural innovations. For this reason, DT systems need to be designed with context in mind from the outset. For IITA, this means moving away from simply adapting external models and instead developing solutions grounded in SSA realities. Approaches such as low-cost, offline-capable DT systems are likely to be more practical and scalable. Long-term field-trial and survey data from research organisations, including the CGIAR, IITA, and others, are a major advantage here, enabling the development of models that reflect real farming conditions. By building on this foundation, IITA can help fill a critical gap in the literature and lead efforts to develop DT systems that work for smallholder agriculture. By bringing

Table 5

Region-wise SWOT (strengths, weaknesses, opportunities, and threats) analysis of DT agriculture research and deployment contexts, an interpretive reading of the reviewed corpus and comparative regional literature.

Region	Strengths	Weaknesses	Opportunities	Threats
Europe	Highly integrated IoT, cloud, simulation and AI systems; strong infrastructure and Industry 4.0 support	Controlled-environment, model-crop focus with weak transfer to rainfed smallholder settings	Mature architectures usable as design blueprints for adaptation	Dependence on connectivity and funding unavailable in low-resource regions
East Asia	Leading research output; advanced AI and large-scale sensing; aquaculture strength	Orientation toward high-connectivity, controlled-environment settings	AI and sensing methods adaptable to other contexts	Context specificity limiting direct transfer to low-infrastructure settings
India and Brazil	Affordable open-source hardware and low-cost cloud; practical low-resource pathway	Lower system integration and maturity	Low-cost designs aligned with SSA offline-first needs	Fragmented solutions with limited scaling and integration support
Sub-Saharan Africa	Emerging SSA digital and climate-smart research base; long-term CGIAR and IITA field data	Absence from the DT corpus; no priority-crop coverage; connectivity and FAIR-data gaps	Open field for context-tailored, offline-first DT; SSA-DT framework as a synthesis-derived entry point	Persistent infrastructure, data and funding constraints; risk of importing ill-fitting external models

digital technologies into agriculture, DT systems can also help reposition the sector as more innovative and appealing, particularly for the youth, opening new opportunities for skills development and employment. Notable progress has been made in developing FAIR (Findable, Accessible, Interoperable, and Reusable) data corpora to support AI and DT applications in agriculture; however, current data availability, quality, and coverage remain insufficient to fully unlock the potential of these technologies in SSA. Significant gaps persist in terms of spatial representativeness, temporal continuity, standardised formats, and integration across agronomic, environmental, and socio-economic datasets. There is therefore a clear need for increased investment and coordinated efforts to build comprehensive, high-quality agricultural data ecosystems. Standardising heterogeneous inputs into model-ready packages for spatial crop modelling, demonstrated across multiple frameworks in West African settings, is one route towards such data ecosystems [52].

4.4. Regional lessons from the global evidence base

The geographic concentration described above allows the regional evidence to be interpreted comparatively. Taken together, each region offers SSA lessons rather than templates for direct transfer (Table 5). Europe's mature, integrated stack (Section 3.7) provides a useful long-term design reference, but it depends on levels of connectivity and investment that remain uneven across much of SSA. East Asia, represented here by national evidence from China, provides some of the clearest empirical evidence linking agricultural digitalisation to stronger climate resilience [53]. Low-cost, open-source approaches from India and Brazil appear more directly aligned with an offline-first pathway suited to many SSA contexts. Recent reviews of digital agriculture in SSA document a growing evidence base [54,55], but this literature remains limited in its treatment of DTs specifically. The SSA-DT framework builds on these regional lessons by translating this low-cost pathway into a conceptual architecture tailored to SSA's infrastructural and resource constraints.

4.5. The crop and systems misalignment

One of the most striking findings is the complete absence of studies focusing on SSA key food security crops such as maize, cassava, sorghum, millet, cowpea, groundnut, banana, and plantain within the DT agriculture literature. These crops are central to the livelihoods and diets of millions [8], yet they remain outside the current research focus. This gap reflects a broader trend in agricultural R&D, where investment tends to prioritise high-value crops and controlled production systems that offer quicker and more visible returns. The contrast is clear: most DT studies focus on crops like tomato, wheat, and lettuce, often grown in controlled environments with stable con-

ditions that support dense sensor networks and reliable connectivity. In comparison, SSA farming systems are more complex, typically rainfed, multi-crop, and highly variable, with limited infrastructure and greater exposure to climatic and market uncertainties. This highlights a deeper challenge: DT systems cannot simply be transferred across contexts. Instead, their design must be rethought to function in heterogeneous, low-connectivity environments. The proposed SSA-DT framework responds to this by prioritising the shadow-twin architecture as a practical entry point. The gradual progression toward predictive and autonomous systems aligns with observed TRL patterns, offering a realistic pathway for scaling DT applications in smallholder agriculture.

4.6. Architectural typologies and the path to SSA relevance

The dominance of predictive twin architectures [11,56] in the literature, combined with the near-exclusive concentration of autonomous twin implementations in controlled-environment settings [57], suggests that the field has reached a broad consensus on the feasibility of simulation-based decision support while recognising that full autonomous control remains aspirational except in the most infrastructure-rich contexts. For SSA, the shadow-twin typology is the most feasible and least infrastructure-demanding architecture and offers the most immediate deployment pathway, consistent with findings from analogous experiences in agricultural IoT deployment in low-resource settings [15,40]. The key insight from the typology analysis is that shadow DT deployment is not a compromise or a stepping stone to be transcended as quickly as possible, but a genuinely valuable intervention in its own right: continuous, multi-sensor state estimation of a farming system provides a quality of operational intelligence that substantially exceeds the status quo of infrequent, survey-based agricultural monitoring that characterises most NARS data systems in SSA. The ability to track soil moisture dynamics, detect crop stress events in near-real-time, and maintain a continuously updated record of field conditions constitutes a fundamental upgrade to the informational infrastructure of smallholder agriculture, irrespective of whether predictive simulation or autonomous control is subsequently added. The technology stack analysis reinforces this conclusion. The near-universal presence of IoT sensor infrastructure as the foundational layer of DT systems reflects a convergence of expert opinion that continuous data acquisition is the non-negotiable architectural prerequisite for any functional DT. This finding directly informs the SSA-DT hardware specification: investment in affordable, rugged, solar-powered IoT sensor kits designed for tropical calibration conditions and capable of operating with intermittent or no connectivity through offline data caching is the highest-priority hardware investment for an SSA DT programme, preceding investment in AI/ML components, cloud infrastructure, or remote sensing integration.

4.7. The human layer: correcting the automation bias in DT architecture

One of the most significant contributions of the proposed SSA-DT control framework to the existing DT architecture literature is its explicit treatment of human agency as a first-order architectural component rather than an implicit deployment context. The absence of farmers, extension agents, and NARS officers from virtually all DT architecture diagrams in the reviewed literature, including seminal contributions presented in Pylianidis et al. [9] and Verdouw et al. [19], encodes what might be termed an “automation bias”: the tendency to conceptualise DT systems as machine-to-machine control loops in which human decision-making is either absent or reducible to a simple interface interaction. This bias is understandable in the engineering and computer science contexts where DT technology originated, such as manufacturing processes, aerospace systems, and smart city infrastructure, where the physical system being twinned is itself a machine whose parameters can be directly controlled by automated actuators. It becomes challenging, however, when transposed to smallholder agricultural contexts where the “physical system” is not a machine but a social-ecological system in which farmer agency, household decision-making, market relationships, and cultural practices are constitutive of system behaviour rather than noise to be filtered out. The publication of a dedicated systematic review of human digital twins in agriculture [58] signals growing scholarly attention to the explicit representation of human factors in DT systems.

The human layer, as articulated in the SSA-DT framework, positioned between the DT engine and farm action, with explicit routing of unforecastable disturbances (market shocks, pest outbreaks, social disruptions) to human decision-makers rather than to the modelling engine, is not merely a concession to the SSA context but a theoretically grounded correction of a conceptual error in the mainstream DT architecture literature. It reflects a systems-design philosophy aligned with the prototype described by Leeuwis et al. [59] as “responsible innovation” in agricultural technology: the recognition that technologies designed without the people who use them, for systems in which those people are central actors, will systematically fail to deliver anticipated benefits regardless of their technical sophistication.

The three nested feedback loops (IoT real-time, DT model update, and MELIA learning) further distinguish the proposed framework from conventional DT architectures by acknowledging that agricultural systems operate simultaneously across multiple temporal scales, and that the appropriate institutional response to information generated at each scale is fundamentally different. Sensor anomaly data require rapid operational response; seasonal yield and dietary diversity performance data require model recalibration; and multi-year programme evidence requires strategic reconsideration of the KPI targets themselves. Conflating these timescales into a single feedback loop, as most DT architecture diagrams implicitly do, produces a control architecture that is either too slow to respond to operational crises or too noisy to support strategic learning.

4.8. Dietary diversity and climate resilience as dual outcome dimensions

The decision to focus on improving diet and climate resilience as the two main outcome dimensions of the SSA-DT framework is deliberate. It aligns with IITA’s 2024–2030 Strategy and reflects what the broader evidence shows about meaningful agricultural impact in SSA. Dietary diversity is captured through indicators such as HFIAS and HDDS, while climate resilience is reflected in measures like yield stability and water-use efficiency. These choices are well grounded in existing food security and impact measurement frameworks [60,61]. The current evidence is stronger for climate-resilience-related outcomes, including water-use efficiency, than for direct food-security outcomes. Validated irrigation twins in the reviewed corpus improved water-use efficiency [41,43]. The national-scale evidence discussed in Section 4.4 points in the same direction, although it does not isolate the effects of DTs. By contrast, di-

etary diversity remains an intended outcome of the conceptual SSA-DT framework rather than an empirically demonstrated effect of existing DT applications. Bringing these two dimensions together within a single DT system is an important step forward. Most existing DT approaches focus on either productivity or sustainability, and very few connect system outputs to household diet. In contrast, the proposed framework treats farm-level decisions as contributing to both outcomes at the same time. For example, practices like intercropping or the use of drought-tolerant varieties can improve both diet quality and resilience to climate stress. This reflects a broader shift toward nutrition-sensitive agriculture and positions the SSA-DT as more than just a tool for increasing yields. At the same time, combining these outcomes within one system is not straightforward. Indicators like HFIAS and HDDS are based on household surveys and cannot be captured directly through sensors. They require periodic data collection through farmer interactions or extension visits, which introduces delays that do not match the real-time nature of IoT data. This creates a practical tension between fast, continuous monitoring and slower outcome measurement. The framework addresses this by separating the system into different feedback loops. The IoT loop handles real-time, sensor-driven data, while the MELIA loop operates on a slower cycle based on surveys and evaluation data. Even so, integrating these two streams effectively will require careful design and testing in practice.

4.9. Architecture designed for real-world use

The proposed architecture is built with real deployment conditions in mind. The goal is to move beyond theory and develop a practical, field-ready framework that can be tested, validated, and applied under real farming conditions. One of the most important choices is the strong focus on the edge layer. In many SSA settings, internet connectivity is unreliable, expensive, or only available at certain times of the day. Because of this, the system cannot depend on constant cloud access. By running lightweight models directly on local devices, it can still generate useful advice, like irrigation alerts, even when offline. Data can be stored locally and synced later. This “offline-first” approach is simple yet critical, reflecting the realities farmers and field teams face every day.

Another key decision is combining crop models with machine learning. Many DT systems rely mainly on data-driven models, which perform well when large, stable datasets are available but often struggle when conditions shift. This is particularly important in SSA, where weather, soils, crop management, and input use vary significantly across locations and seasons. By adding crop simulation models calibrated with IITA’s long-term field data, the system becomes more reliable and robust. This hybrid approach can better represent crop growth processes, handle uncertainty, and still learn from new data, making predictions more useful for real-world field and farmer conditions [40,42]. Extending models calibrated at a few sites across this variability requires quantifying agroecological similarity between locations, for which computational methods are available [62].

The way the system is delivered to users also matters. Instead of a one-size-fits-all interface, the design includes three: a web dashboard for managers and researchers, a mobile app for farmers and extension agents, and a separate interface for technical testing. This makes the system easier to use for different groups. The mobile app is designed to work offline and support local languages, so farmers can benefit from it directly rather than relying on intermediaries. This aligns with IITA’s focus on inclusion and access [63]. This architecture is grounded in practical realities. It prioritises what will work, not just what is technically possible, making it better suited for smallholder farming systems. A recent framework for urban agriculture adopts outcome-oriented DT design [64], although its practical effects remain to be validated.

4.10. Limitations

Several limitations of this study warrant acknowledgement. The English-language restriction imposed on the systematic search may have excluded relevant DT agriculture publications in Chinese, French, Portuguese, and other languages, potentially underestimating the contribution of Chinese and Francophone research communities. The TRL scores assigned to each study represent reviewer-assessed proxy ratings rather than author-reported or independently verified assessments, introducing a degree of subjectivity that, while mitigated by the inter-rater reliability protocols, cannot be fully eliminated. Further, the proposed SSA-DT framework remains at TRL 2–3: it is a conceptual architecture informed by evidence synthesis, not a validated deployment blueprint. The transition from framework to prototype will require substantial empirical investment in crop model parameterisation, sensor hardware calibration, and multi-season field validation that lies beyond the scope of the present study. In addition, the binary treatment of disturbances as either forecastable or unforecastable oversimplifies a continuum of predictability; some shocks (e.g., seasonal pest pressure, near-term price trends) occupy intermediate zones that the current architecture does not explicitly accommodate. Finally, the proposed KPI operationalisation, while grounded in established food security measurement frameworks, does not address the full complexity of household dietary decision-making, which is shaped by cultural, social, and economic factors that extend beyond what any DT system can monitor or model.

4.11. Implications for research and policy

The findings of this study carry implications that extend beyond IITA's institutional programme to the broader agricultural R&D and development finance communities. The systematic absence of SSA from the DT agriculture evidence base is not a problem that IITA or any single institution can resolve alone; it reflects a structural misalignment in global agricultural R&D investment that requires a coordinated response from CGIAR, bilateral donors, and national governments. Three priority actions are recommended. First, the CGIAR's 2030 Research and Innovation Strategy and its successor frameworks should explicitly include DT technology for smallholder agriculture as a fundable research category, with SSA contextualisation as a non-negotiable requirement for funded projects. The current absence of multilateral development finance from the DT agriculture corpus is not a reflection of the technology's irrelevance to development priorities but of a funding architecture that has not yet recognised its potential. Second, North–South research partnerships pairing European DT technical expertise with SSA institutional context knowledge should be prioritised in EU Horizon Africa partnership programmes, with IITA serving as the SSA anchor institution. Such partnerships offer the fastest pathway to advancing the SSA-DT prototype from TRL 3 to TRL 5, drawing on the accumulated technical competence of WUR and Aristotle University while grounding system design in IITA's field reality. Third, national agricultural research and extension systems across SSA should be engaged as institutional co-owners of DT data infrastructure from the outset of any deployment programme, not as implementation partners to be brought in at the scaling stage. A further priority is the deliberate consideration of ethical and societal issues during the design and deployment of DT systems [31]. This means explicitly factoring in stakeholder engagement through human-centred design, anticipating possible unintended consequences, and accounting for the welfare of non-human actors such as animals that form part of the wider biodiversity in agroecosystems. A deliberate investment in the collection and sharing of big data in agriculture following FAIR principles is also essential: accessibility of reliable data is a prerequisite for generating DTs tuned to the local context. The data governance and institutional embeddedness principles articulated in the proposed framework, specifically the principle that NARS should hold national data sovereignty and institutional ownership of

the data hubs, are not merely ethical aspirations but practical prerequisites for long-term system sustainability after external research funding ends.

CRedit authorship contribution statement

Henri E.Z. Tonnang: Writing – original draft, Methodology, Data curation, Conceptualization; **Francis Chianu:** Formal analysis, Data curation; **Siyabusa Mkuhlani:** Writing – original draft, Methodology, Formal analysis; **Francis Muthoni:** Writing – original draft, Methodology, Formal analysis; **John Michael Humphries Choptiany:** Writing – original draft, Methodology, Formal analysis; **Franck B.N. Tonle:** Writing – original draft, Methodology, Formal analysis; **Bonoukpoe M. Sokame:** Writing – original draft, Methodology, Formal analysis; **Mercy Lung'aho:** Writing – original draft, Methodology, Data curation, Conceptualization.

Informed consent

Not applicable. The study involved no human participants and used no individual or identifiable personal data, so informed consent was not required.

Consent for publication

Not applicable. The manuscript contains no individual person's data in any form.

Ethical approval

Not applicable. This work is a review of published literature and did not involve any new studies of, or the collection of primary data from, human participants or animals performed by any of the authors. Ethical approval was therefore not required, and no ethics committee reference number or approval date applies.

Ethics declaration

The author(s) declare(s) that the study does not involve humans nor animal subjects.

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Data

All data analysed in this review were obtained from the publicly available, previously published studies cited in the manuscript. The authors confirm that this work was conducted in accordance with Elsevier's research ethics policy.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Supplementary material

Supplementary material associated with this article can be found in the online version at [10.1016/j.atech.2026.102532](https://doi.org/10.1016/j.atech.2026.102532).

Appendix A. Supplementary materials

The full extraction workbook (PRISMA_Digital_Twin_Agriculture.xlsx) is provided as a separate Excel file accompanying this manuscript. A complete list of the abbreviations used in this article is provided in [Table A.1](#).

Table A.1
Abbreviations used in this article.

Abbreviation	Definition
AI/ML	Artificial intelligence/machine learning
CEA	Controlled environment agriculture
CGIAR	Consultative Group on International Agricultural Research
DOI	Digital object identifier
DT	Digital twin
FAIR	Findable, Accessible, Interoperable, and Reusable
GIS	Geographic information system
HDDS	Household Dietary Diversity Score
HFIAS	Household Food Insecurity Access Scale
ICC	Intraclass correlation coefficient
IITA	International Institute of Tropical Agriculture
IoT	Internet of Things
KPI	Key performance indicator
MELIA	Monitoring, Evaluation, Learning, and Impact Assessment
NARS	National agricultural research systems
NASA	National Aeronautics and Space Administration
P4D	Partnerships for Delivery
PICOS	Population, Intervention, Comparison, Outcomes and Study
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
R4D	Research for Development
SSA	Sub-Saharan Africa
SWIM	Synthesis without meta-analysis
SWOT	Strengths, weaknesses, opportunities, and threats
TRL	Technology readiness level
UAV	Uncrewed aerial vehicle
WUR	Wageningen University & Research

Table A.2
PRISMA-compliant screening and selection flow for the DT agriculture systematic review.

PRISMA stage	Action taken	Records / result	Decision rationale
Identification	Database search (Web of Science, Scopus, IEEE Xplore, Google Scholar) using the Boolean query: (“digital twin*” OR “digital representation” OR “virtual replicate” OR “digital replicate”) AND (“agriculture” OR “farming” OR “agri-food” OR “agrifood” OR “precision agriculture” OR “smart farming” OR “crop” OR “livestock” OR “greenhouse” OR “horticulture” OR “aquaculture” OR “irrigation” OR “food supply chain”)	<i>n</i> = 213 unique records after duplicate removal	Broad query intentionally inclusive to minimise Type II error at this stage
Screening (title/abstract)	Title and abstract screening by a primary reviewer, with 20% of records independently screened by a second reviewer	<i>n</i> = 112 excluded (not DT-specific; not agriculture domain)	Inter-rater agreement checked on the 20% sample; disagreements resolved by discussion and consensus
Screening (full text)	Full-text eligibility assessment of remaining records	<i>n</i> = 61 excluded (insufficient methodological detail; DT described peripherally; non-peer-reviewed)	Studies describing DT in passing without architectural or implementation detail were excluded
Inclusion	Final corpus accepted after quality assessment	<i>n</i> = 40 studies included	Screening and selection are summarised in the PRISMA flow diagram (Fig. 1)

Table A.3

Data extraction instrument: variable categories, specific fields, and analytical purpose for each dimension of the structured extraction.

Variable category	Specific fields extracted	Analytical purpose
Bibliometric identifiers	Author name(s), year of publication, article title, journal/conference, language, DOI	Publication growth trajectory; temporal analysis; citation network mapping
Evidence typology	Type of evidence source (peer-reviewed journal, conference paper, systematic review, bibliometric review, book chapter)	Classification of evidence hierarchy; field maturity assessment
Geographic & institutional	Lead author country; co-author countries; institutional affiliation(s); funding source; funding category	Geographic concentration analysis; collaboration network mapping; funding landscape characterisation
Study design	Study design classification (experimental, quasi-experimental, simulation, RCT, conceptual framework, narrative review, systematic review, bibliometric)	Methodological maturity profiling; rigour assessment; comparison against gold-standard designs
Problem / application domain	Primary agricultural problem addressed; application domain (irrigation, CEA, livestock, supply chain, soil management, etc.); crop/species studied	Domain frequency analysis; food security alignment assessment; SSA relevance scoring
Technology stack	Technologies deployed (IoT, AI/ML, cloud/edge/fog, remote sensing, simulation, GIS, blockchain, 3D modelling, UAV)	Technology stack frequency; architectural typology classification; integration depth scoring
Technology readiness level	TRL score (1–9) assigned per study based on deployment context and validation evidence	Technological maturity profiling; TRL distribution analysis; TRL driver identification
Aims & objectives	Verbatim aims statement from abstract/introduction	Thematic clustering; keyword frequency analysis; alignment with IITA programme areas
Key findings	Summary of findings relevant to DT implementation and food security	Cross-study synthesis; identification of converging and diverging evidence
Gaps identified	Author-identified gaps and future research directions	Evidence gap mapping; priority-setting for the SSA-DT research agenda

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